An initial assessment of coupled land-atmosphere *memory* in (*and beyond*) reanalysis

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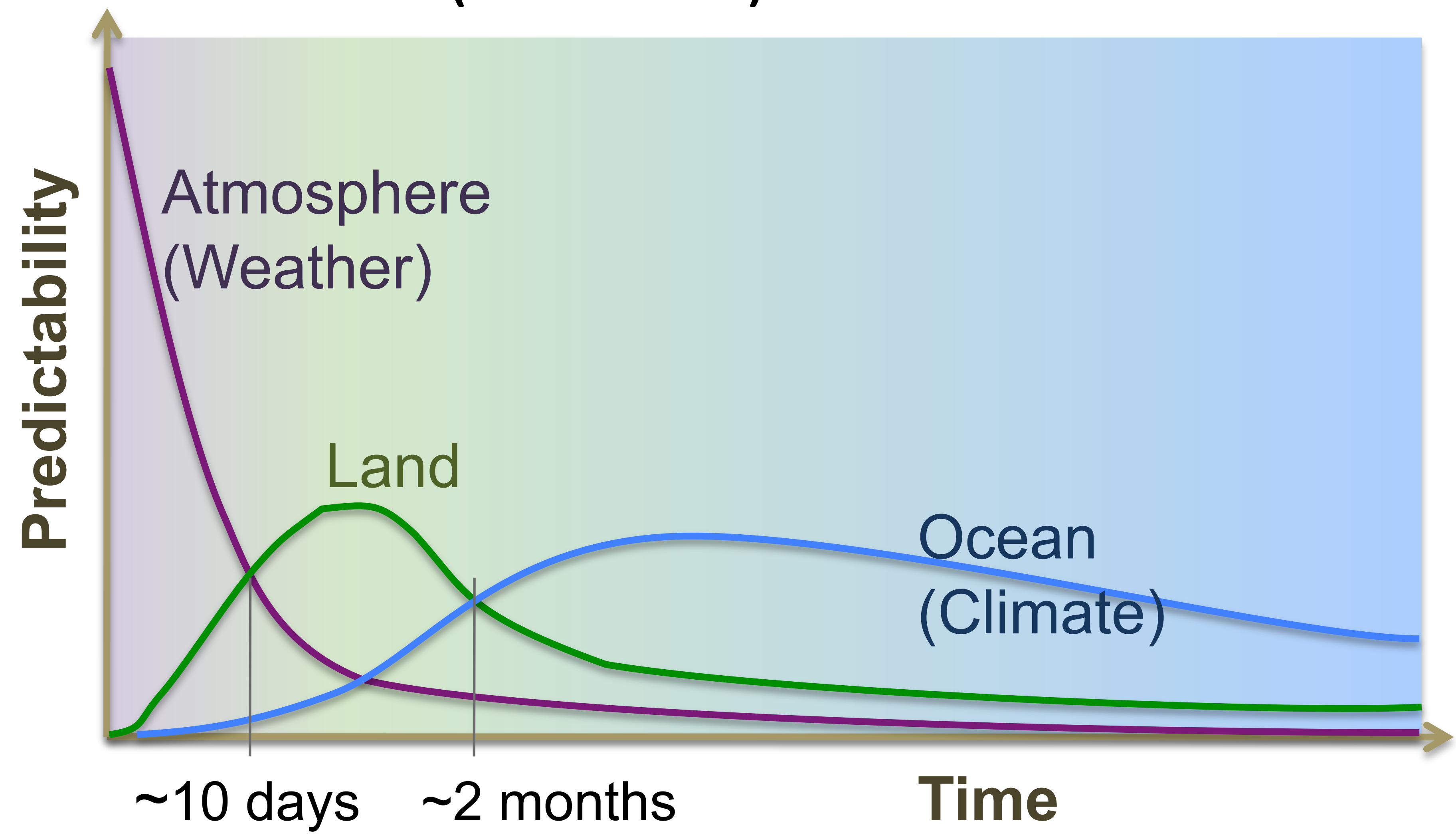
Predictability and Prediction

•Land states (namely soil moisture*) can provide predictability in the window between deterministic (weather) and climate (O-A) time scales.



*Snow too!

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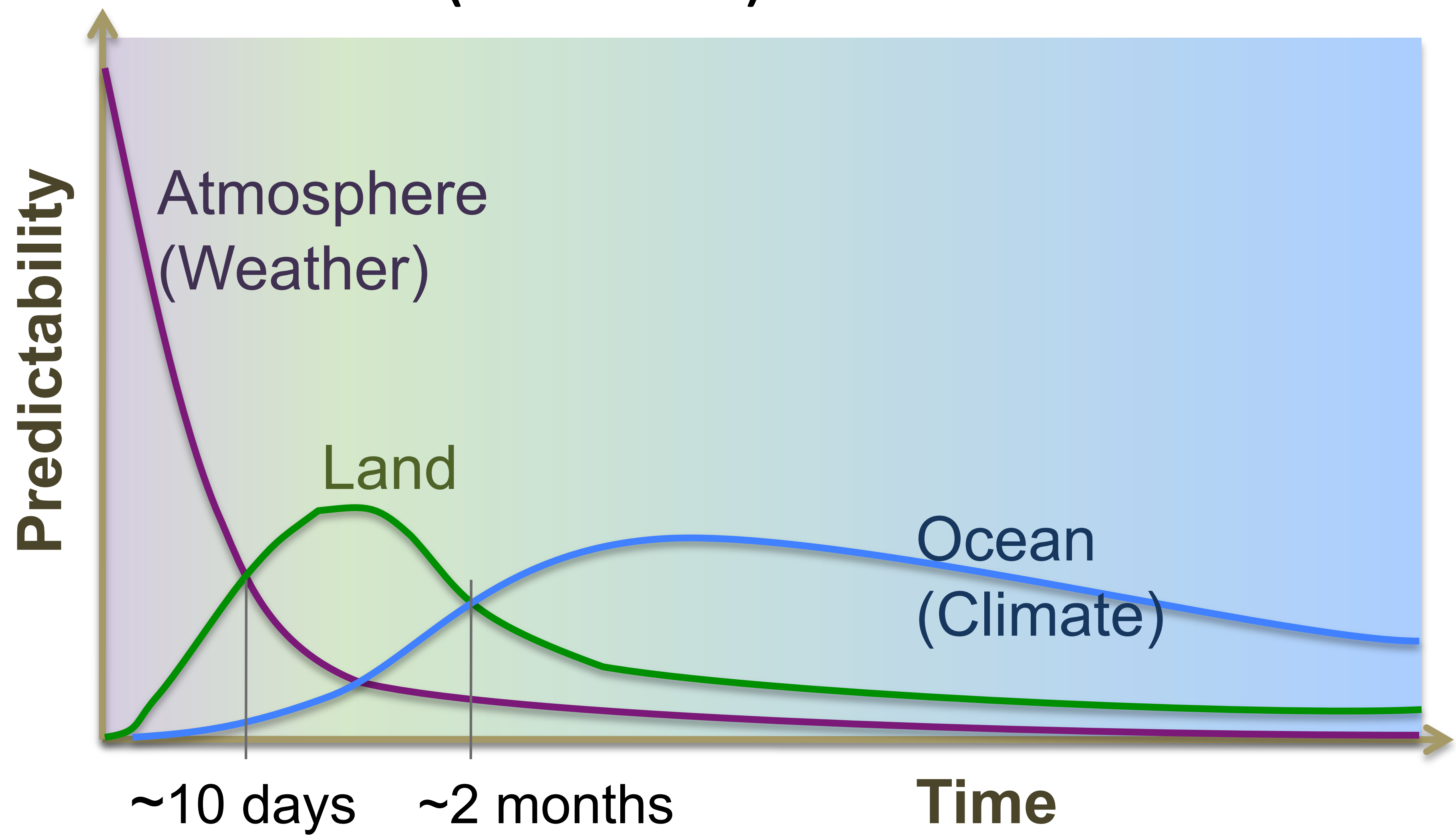
  1. Memory of initial land states



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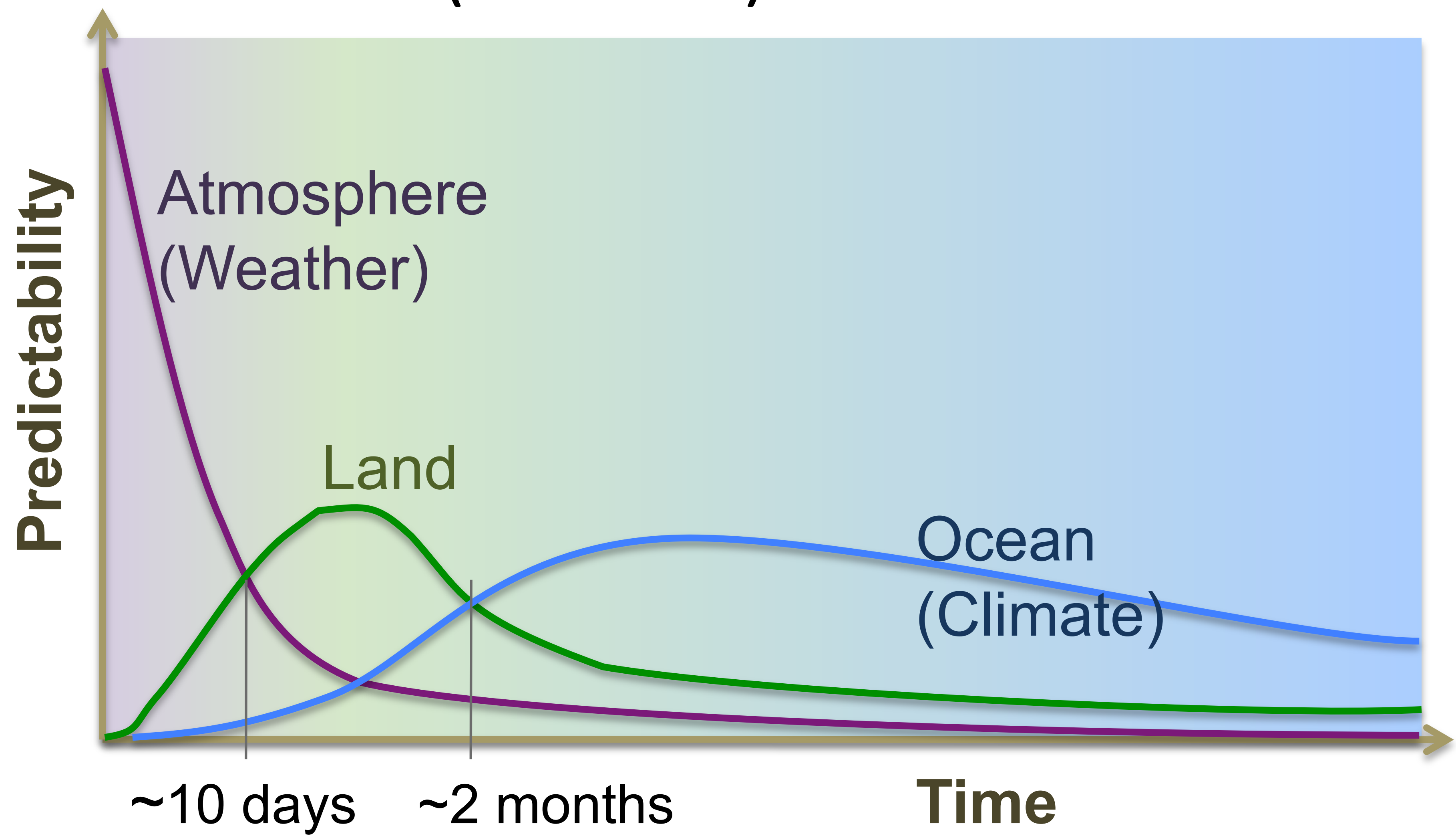

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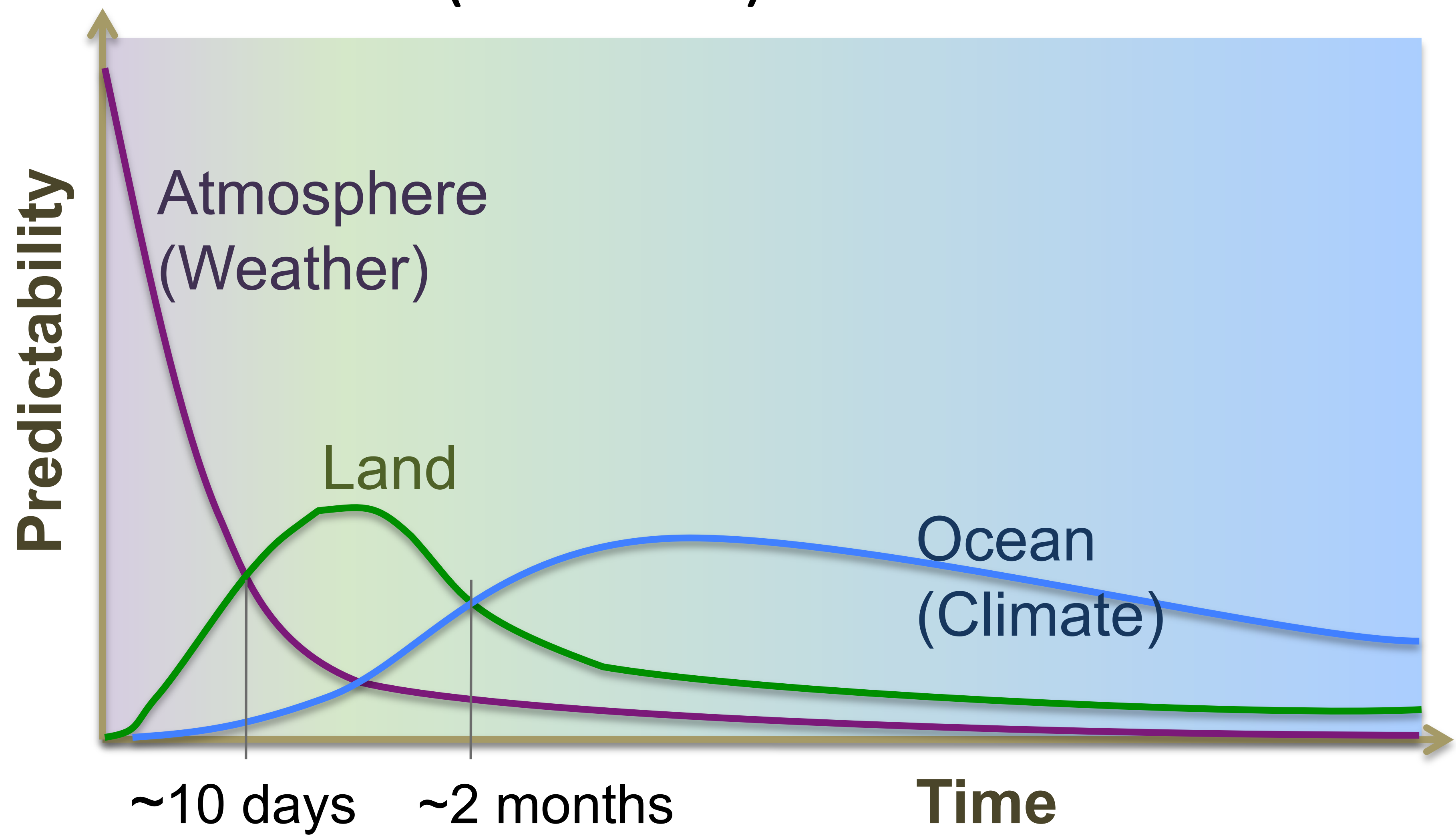

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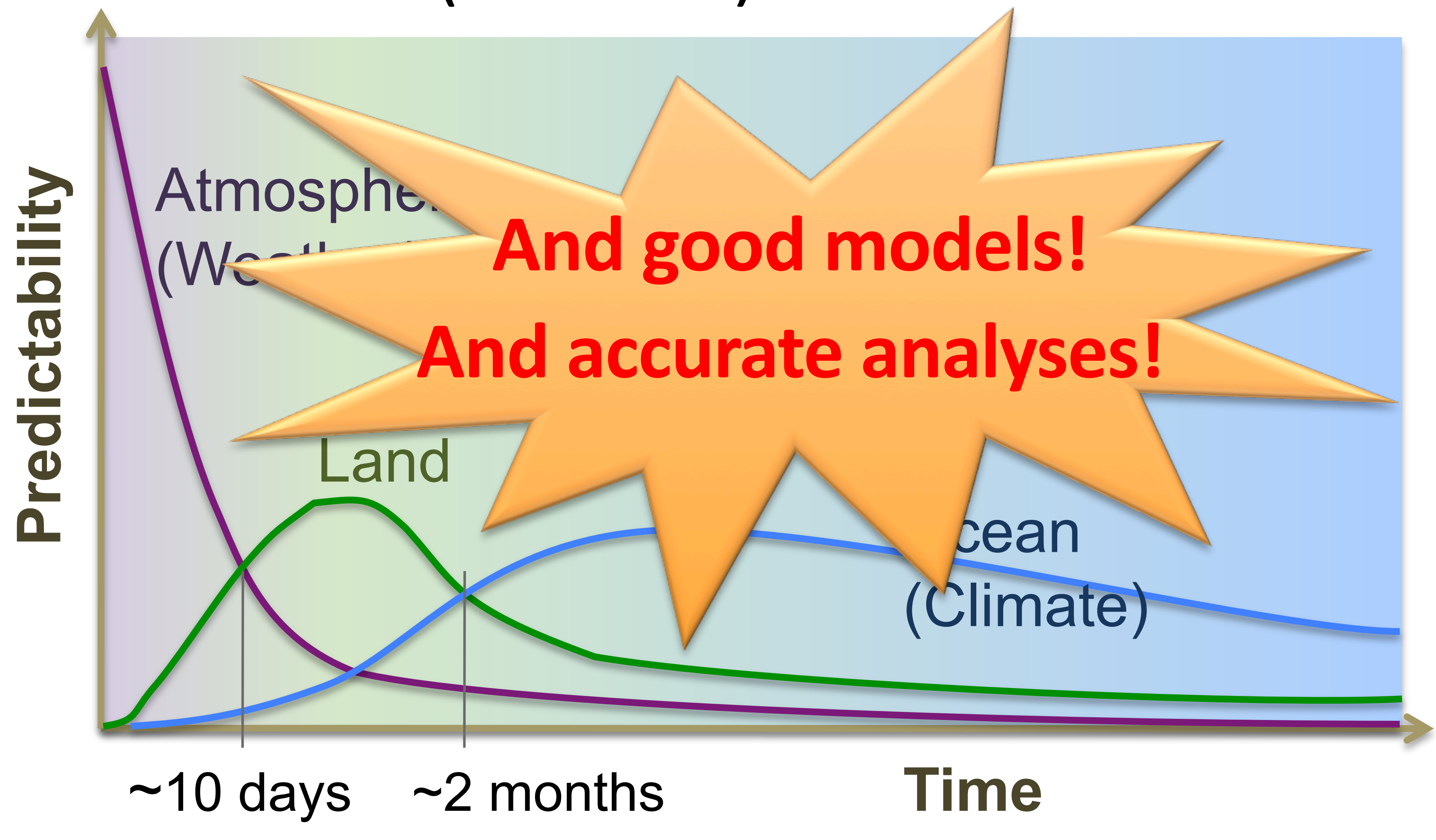

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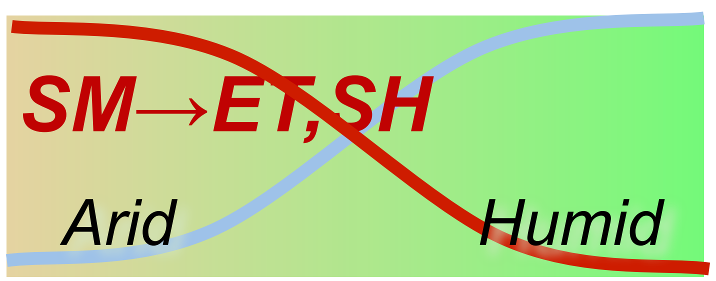
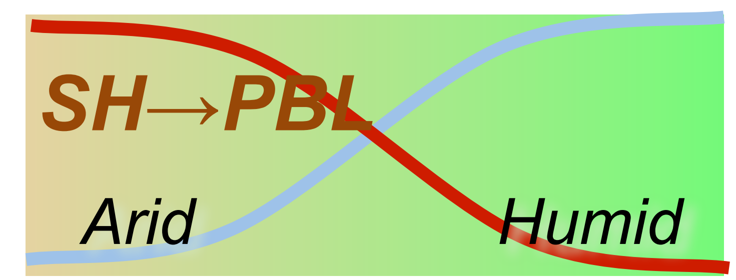
L-A feedback stands on 2 legs

$$\Delta P \rightarrow \Delta SM \rightarrow \Delta Fluxes \rightarrow \Delta PBL \rightarrow \Delta P$$

Feedback path: **Terrestrial leg** **Atmospheric leg**





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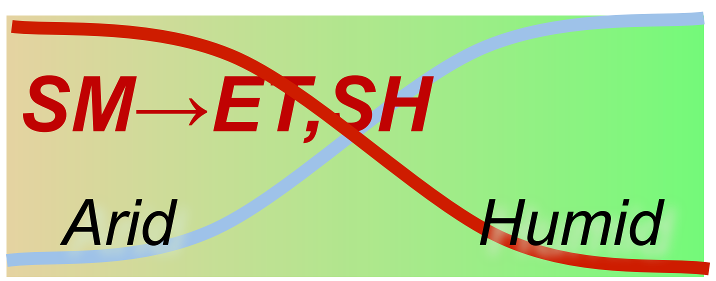

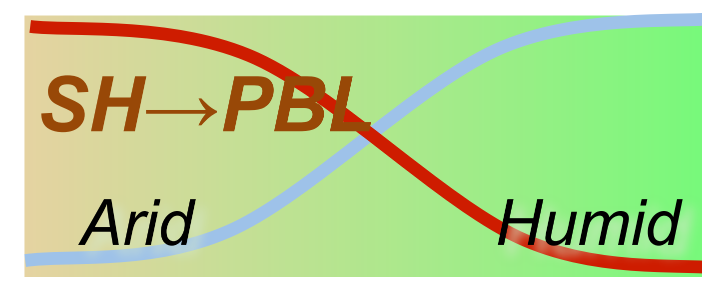

- Terrestrial – When/where does soil moisture (vegetation, snow, etc.) control the partitioning of net radiation into sensible and latent heat fluxes?

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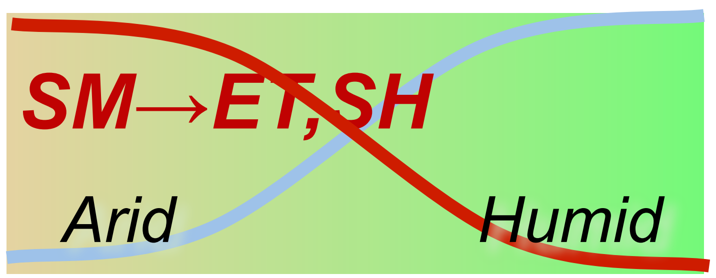

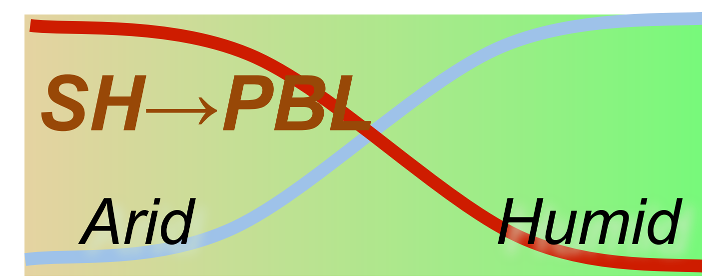

- Terrestrial – When/where does soil moisture (vegetation, snow, etc.) control the partitioning of net radiation into sensible and latent heat fluxes?
- Atmosphere – When/where do surface fluxes significantly affect boundary layer growth, clouds and precipitation?

Observations used

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  - Station must have >100 daily reports during JJA to be included in the analysis.

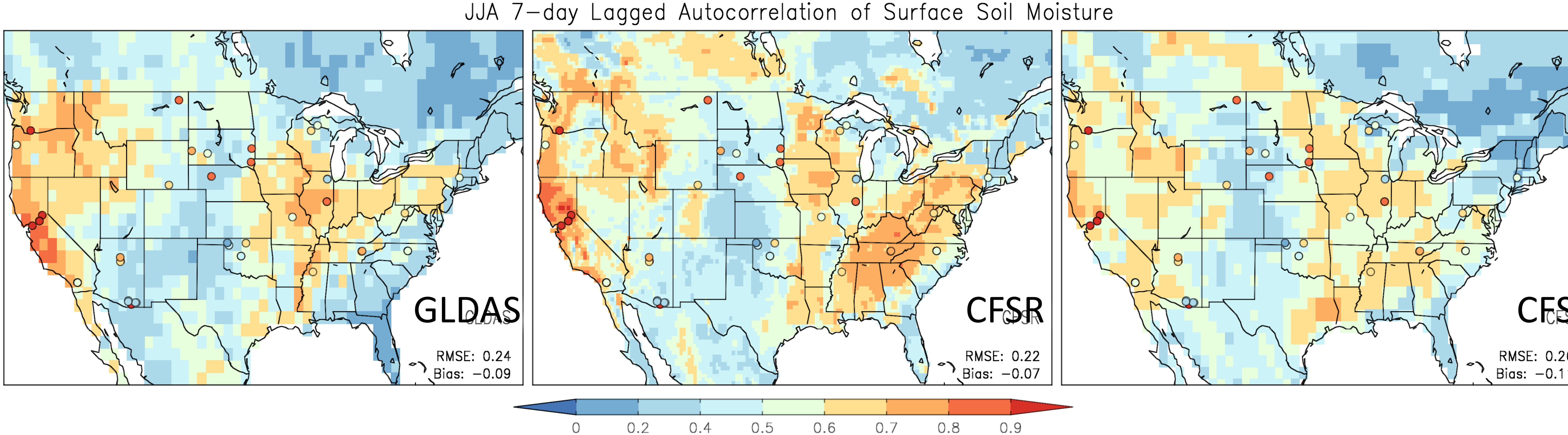
Models / data used

	"Offline" Land model simulations	Atmospheric Reanalyses (constrained by DA)	Free-running GCMs (unconstrained)
NCEP/EMC	Global Land Data Assimilation System Noah2.7 land model All gridded observational forcing 1°x1°	Coupled Forecast System Reanalysis CFSv2 AGCM Noah2.7 land model 0.31°x0.37°	CFS Seasonal Forecasts (JJAS) initialized from CFSR Noah2.7 land model (T126) 0.94°x0.95°
NASA/GSFC/ GMAO	MERRA-Land Catchment land model MERRA + GPCP forcing 0.67°x0.5°	MERRA GEOS5 AGCM Catchment land model 0.67°x0.5°	GEOS5 "AMIP" Simulation Catchment land model 0.67°x0.5°

~30 years for each, covering ~1980s-2000s

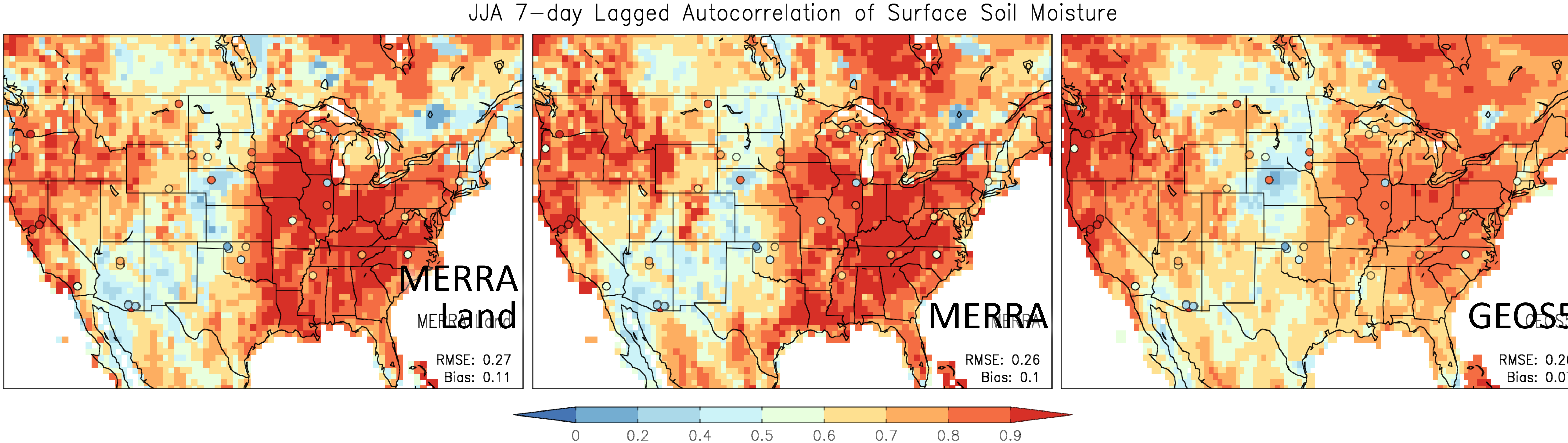
GEOS5 data courtesy: Mike Bosilovich

Surface soil moisture memory



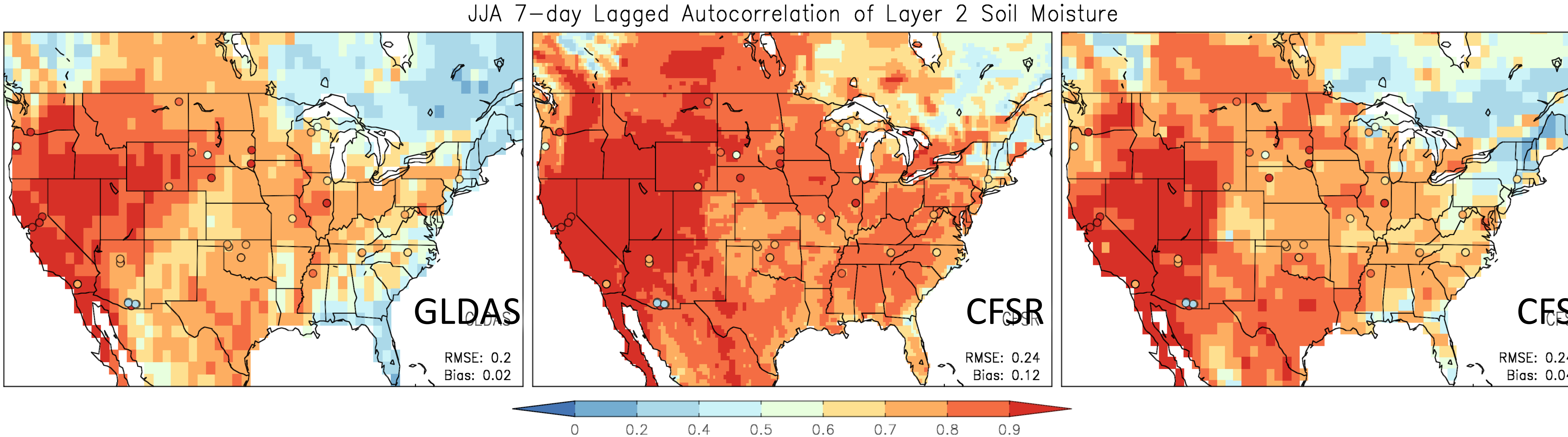
- All versions have shorter memory than AmeriFlux
  - CFS has strongest bias & RMSE – most influenced by AGCM
  - CFSR has lowest bias & RMSE
  - Large errors for all at individual stations
- There are consistency issues (depth of measurements, point vs grid scale)

GSFC Surface soil moisture memory



- For contrast: MERRA/GEOS5 has <u>longer</u> memory than AmeriFlux
  - Very similar pattern to GLDAS/CFSR/CFS over CONUS
  - Lack of memory over Great Plains "hot spot" in both is a general issue for predictability!

Root zone soil moisture memory



- All NCEP versions have longer memory than AmeriFlux
  - GLDAS closest to observations; CFSR largest bias
  - Depth of measurements may be a significant factor (25cm vs 10-15)
  - Large errors for all at individual stations is a more serious factor….
  - “Hole” over Great Plains is less evident

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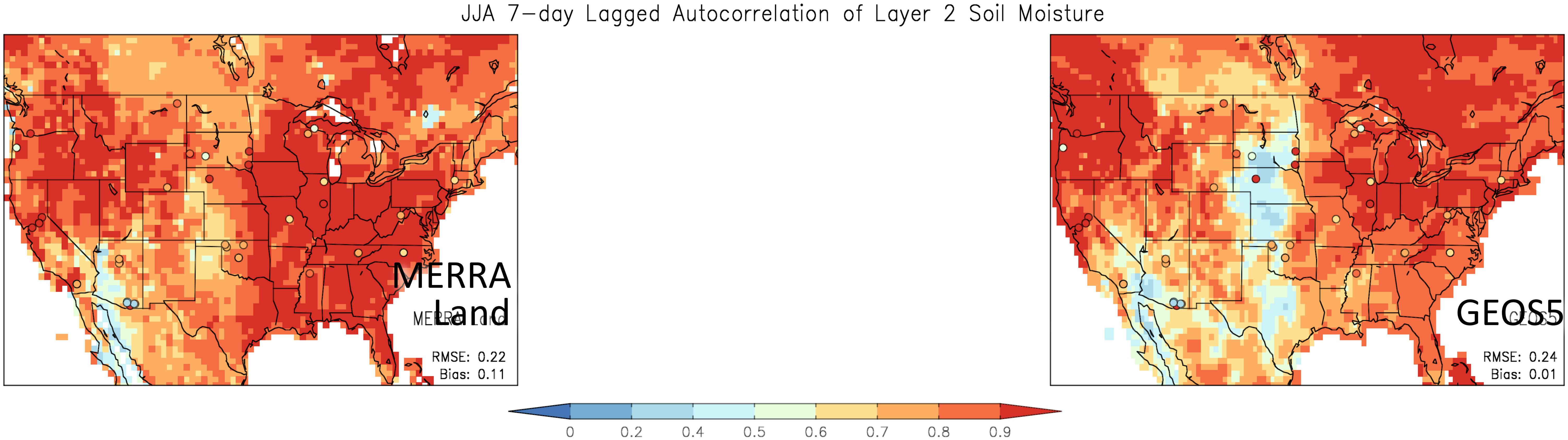
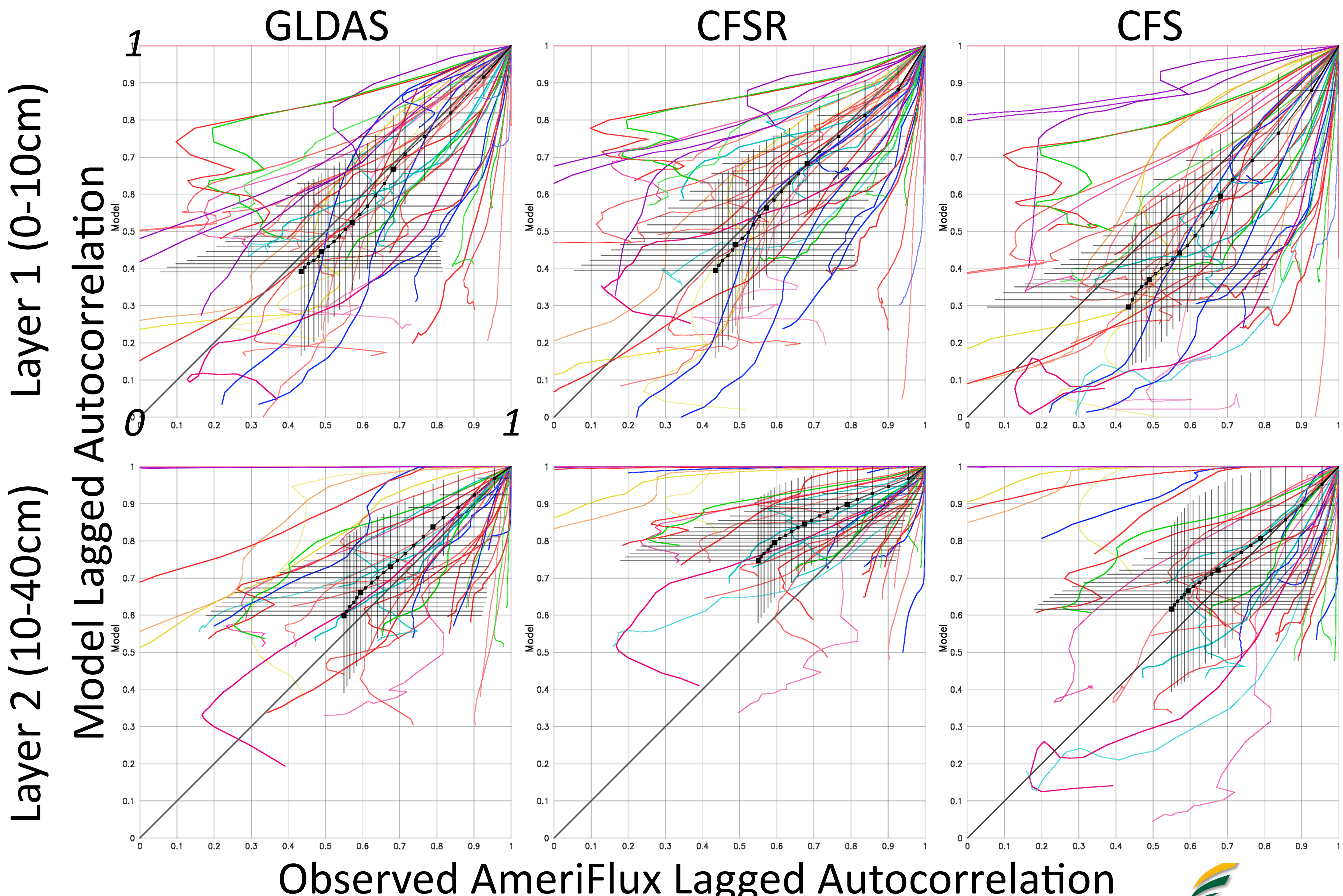


- NASA models maintain that “hole” over Great Plains

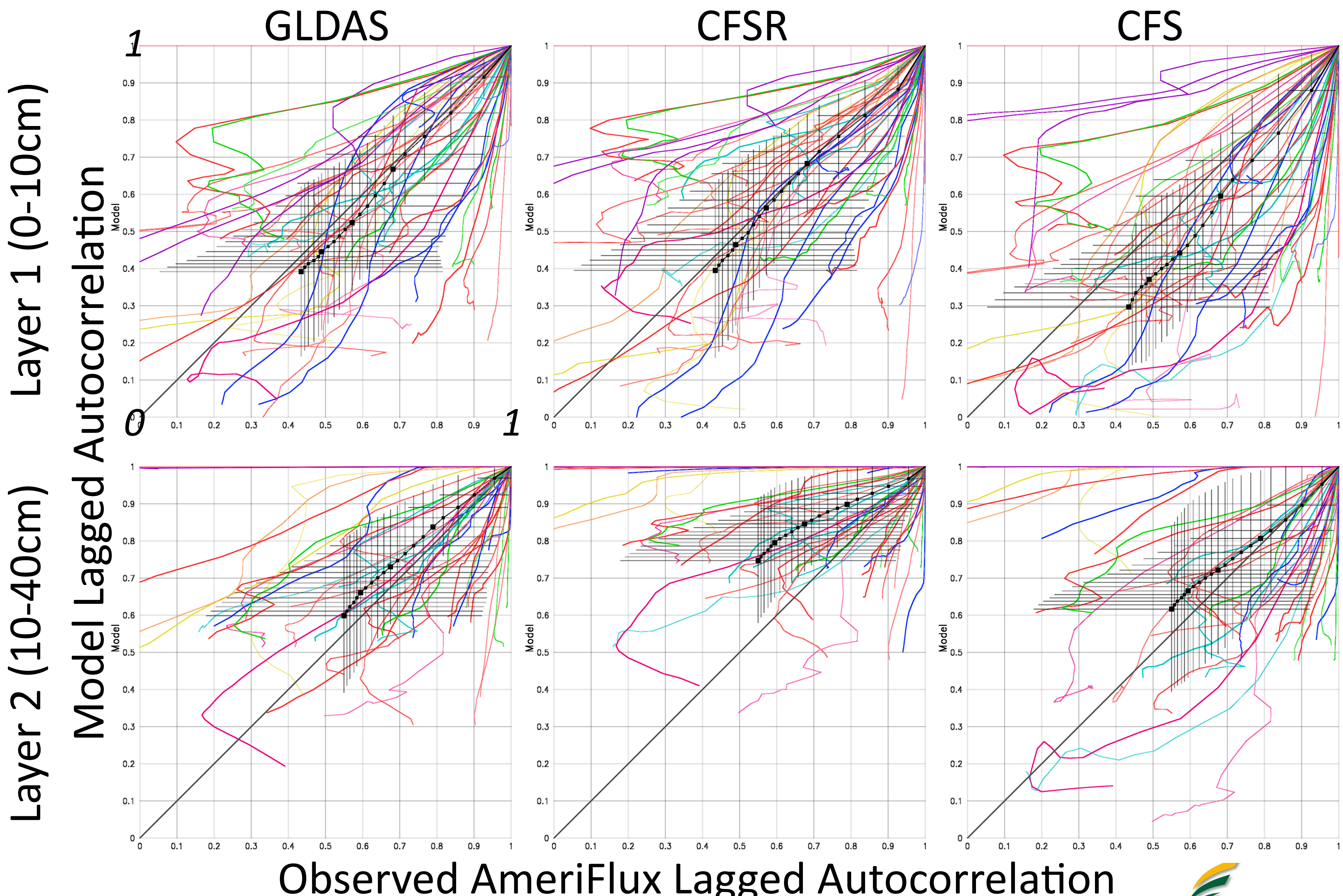
1 to 21 day lagged ACC at 46 stations

- Colored lines are indiv. Stations
- Black line with dots: avg. of 46
- Whiskers: ±1σ
- Diagonal: perfect match
- Caveats about scale, depth still apply.



1 to 21 day lagged ACC at 46 stations

- CFS: too little memory of surface soil moisture*



* *Consistent with finding of Dirmeyer (2013; CFSv2 Special Issue) showing CFS reforecast precip is too noisy, loses its correlation with ICs too quickly.*

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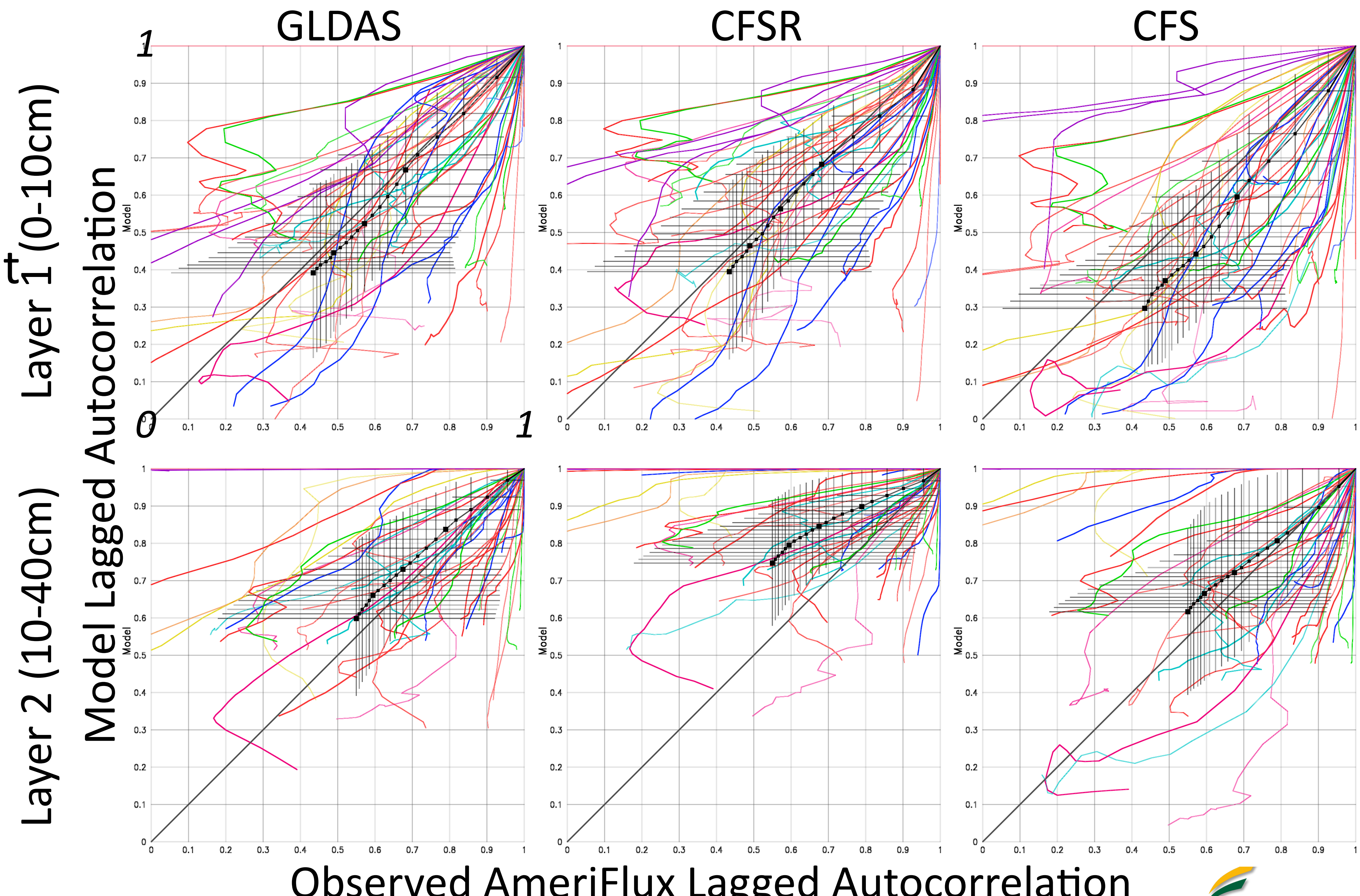
- CFSR very persistent for subsurface soil moisture



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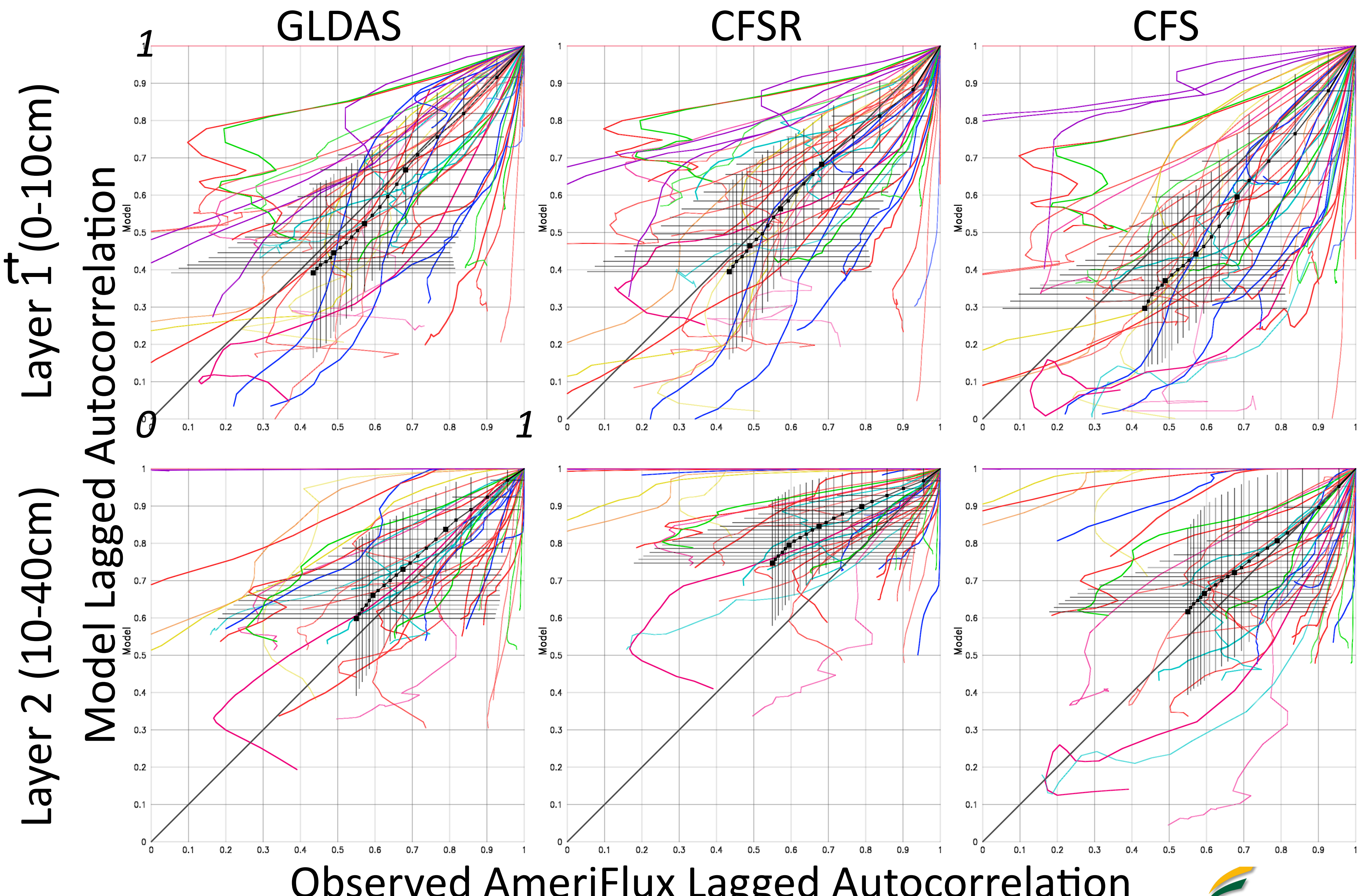
- Too little inter-station spread



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1 to 21 day lagged ACC at 46 stations

- CFS: too little memory of surface soil moisture*
- CFSR very persistent for subsurface soil moisture
- Too little inter-station spread
- Individual stations: all over the place

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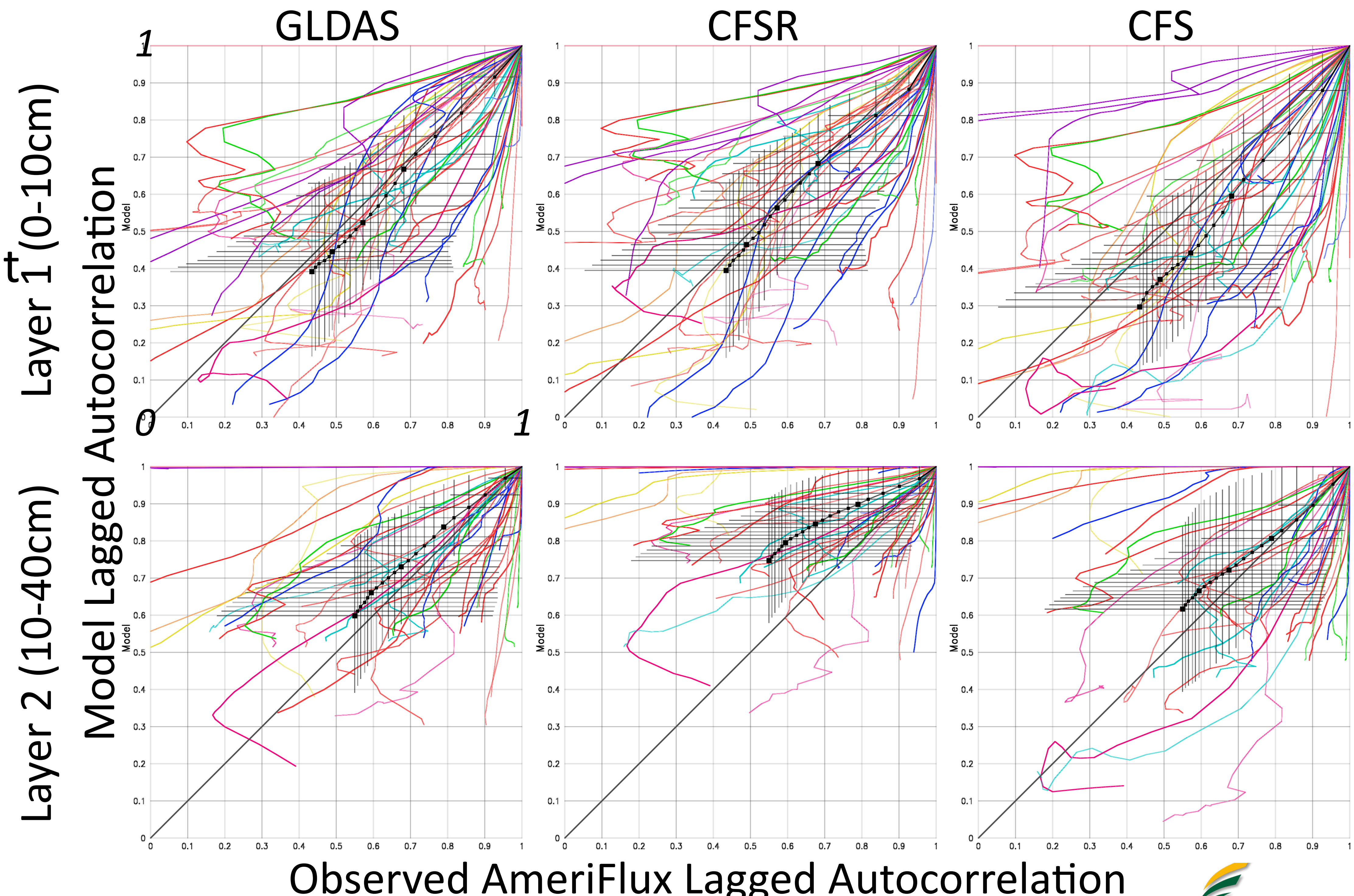
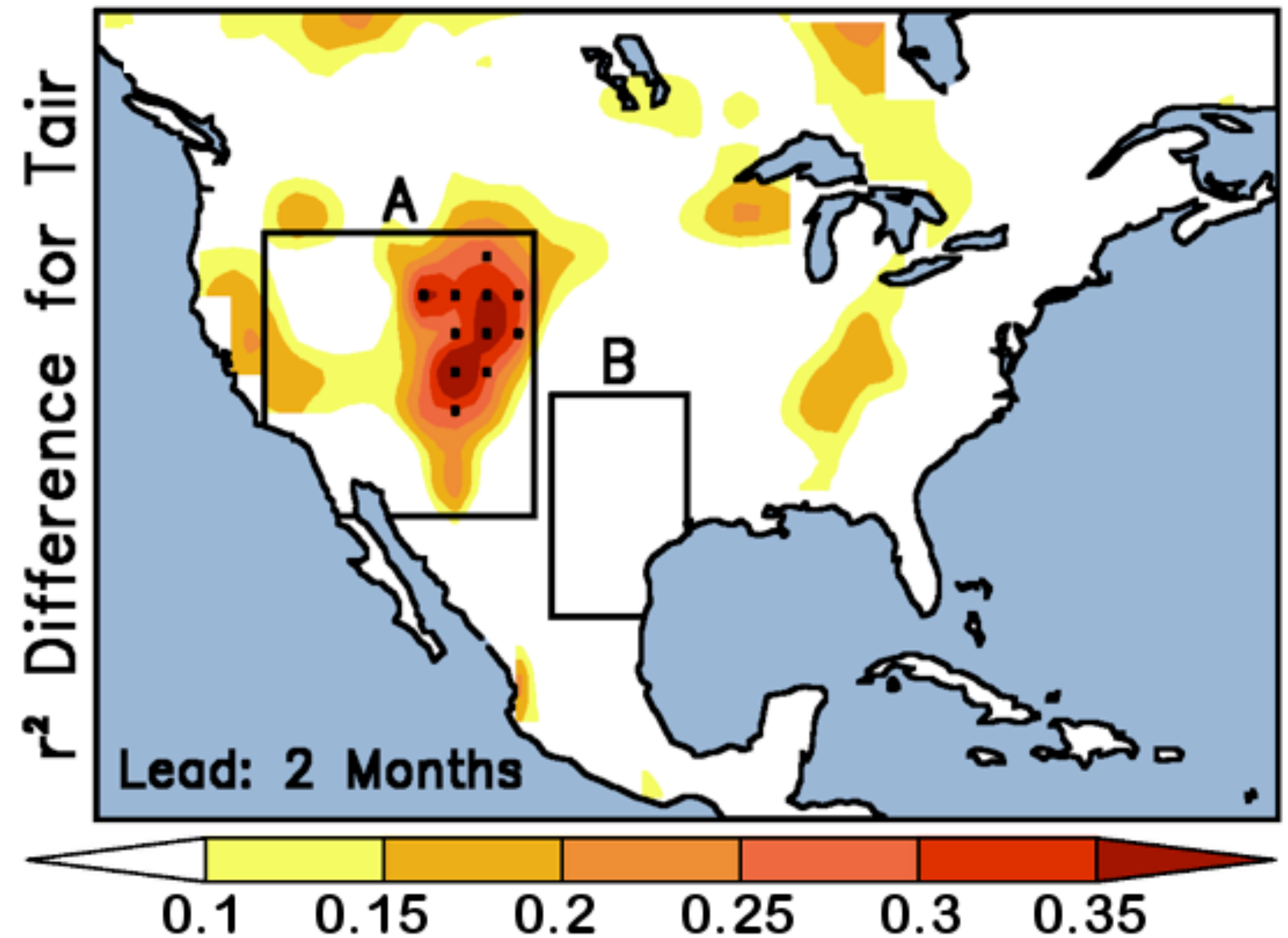


What about that hole?

- In GLACE2 we saw that realistic soil moisture initialization improved T_{2m} forecast skill, especially over North America, but not over the "hot spot" [B].

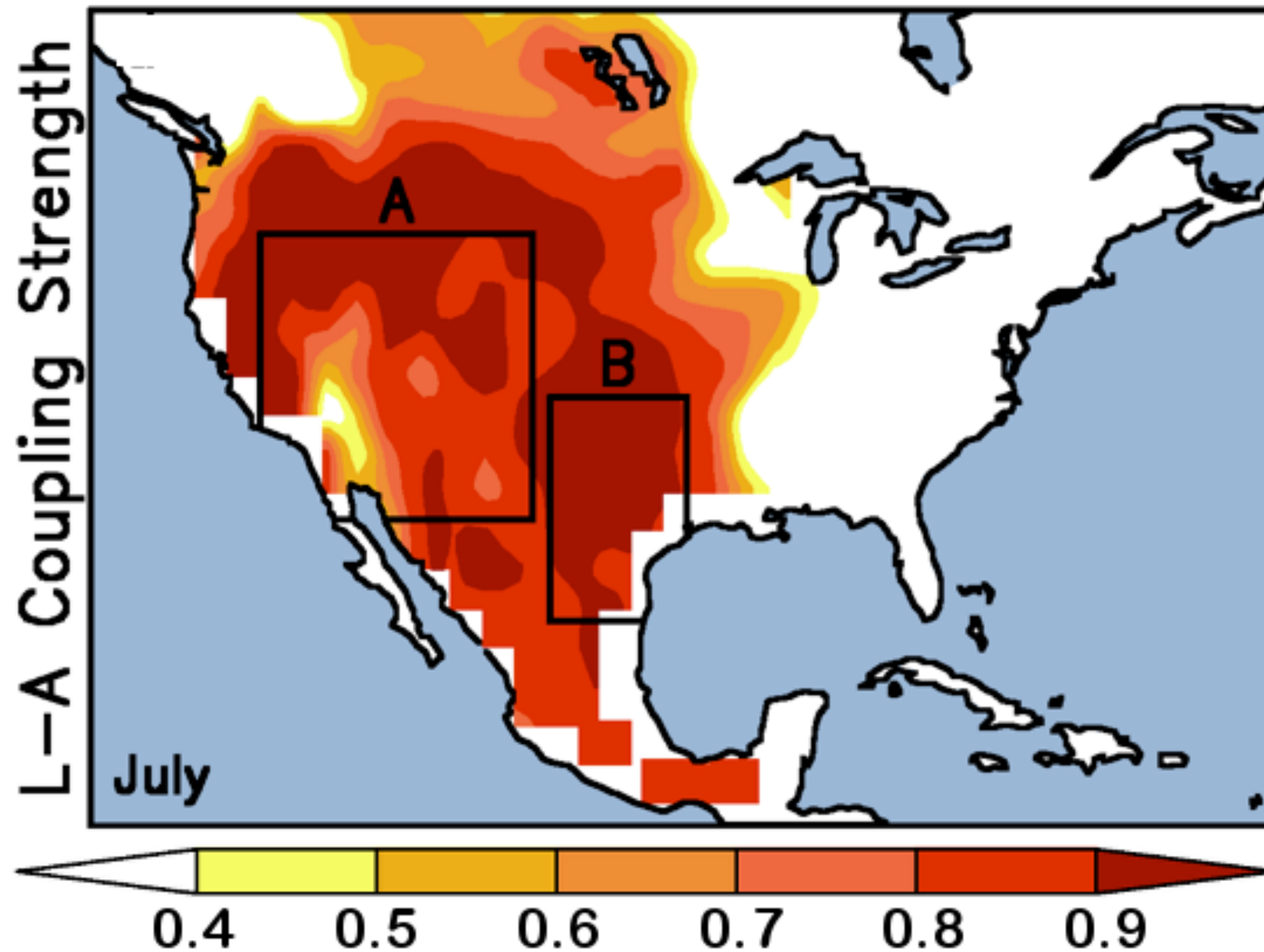


- Figure is for COLA GCM, but conclusion was true for multi-model results as well (Koster et al. 2010).

Koster, R., et al., 2010: *Geophys. Res. Lett.*, **37**, L02402, doi:10.1029/2009GL041677.

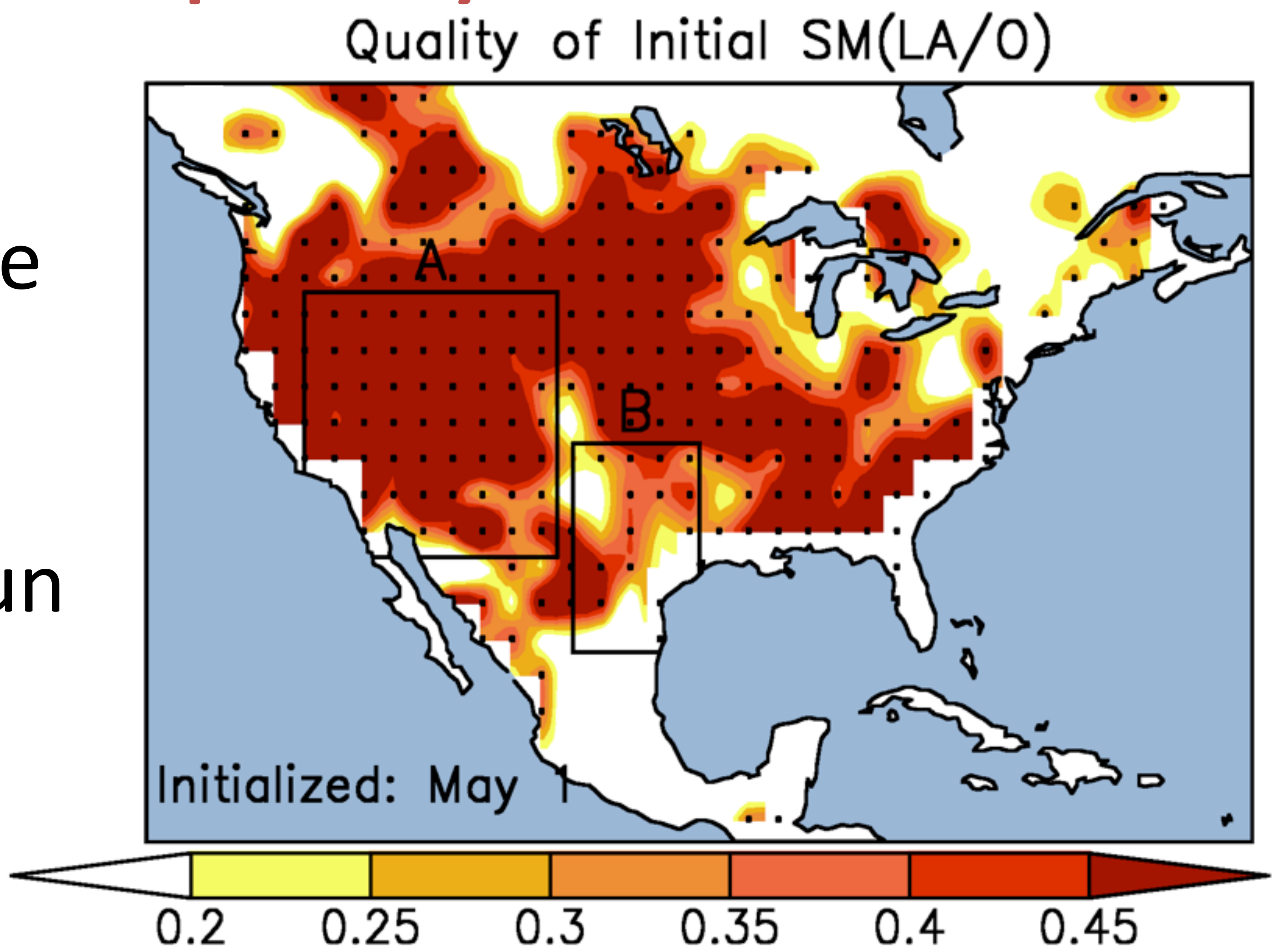
Soil moisture – temperature coupling

- Coupling strength in COLA GCM (this is for temperature; hot spot extends further west than for precipitation).
- Area [B] has strong coupling strength. Why no skill there?



Initial soil moisture quality

- Compared to GLDAS, the initial soil moisture states are pretty good over the US (COLA ICs from an offline SSiB run in style of GSWP-2).
- Initialization does not appear to be the problem.

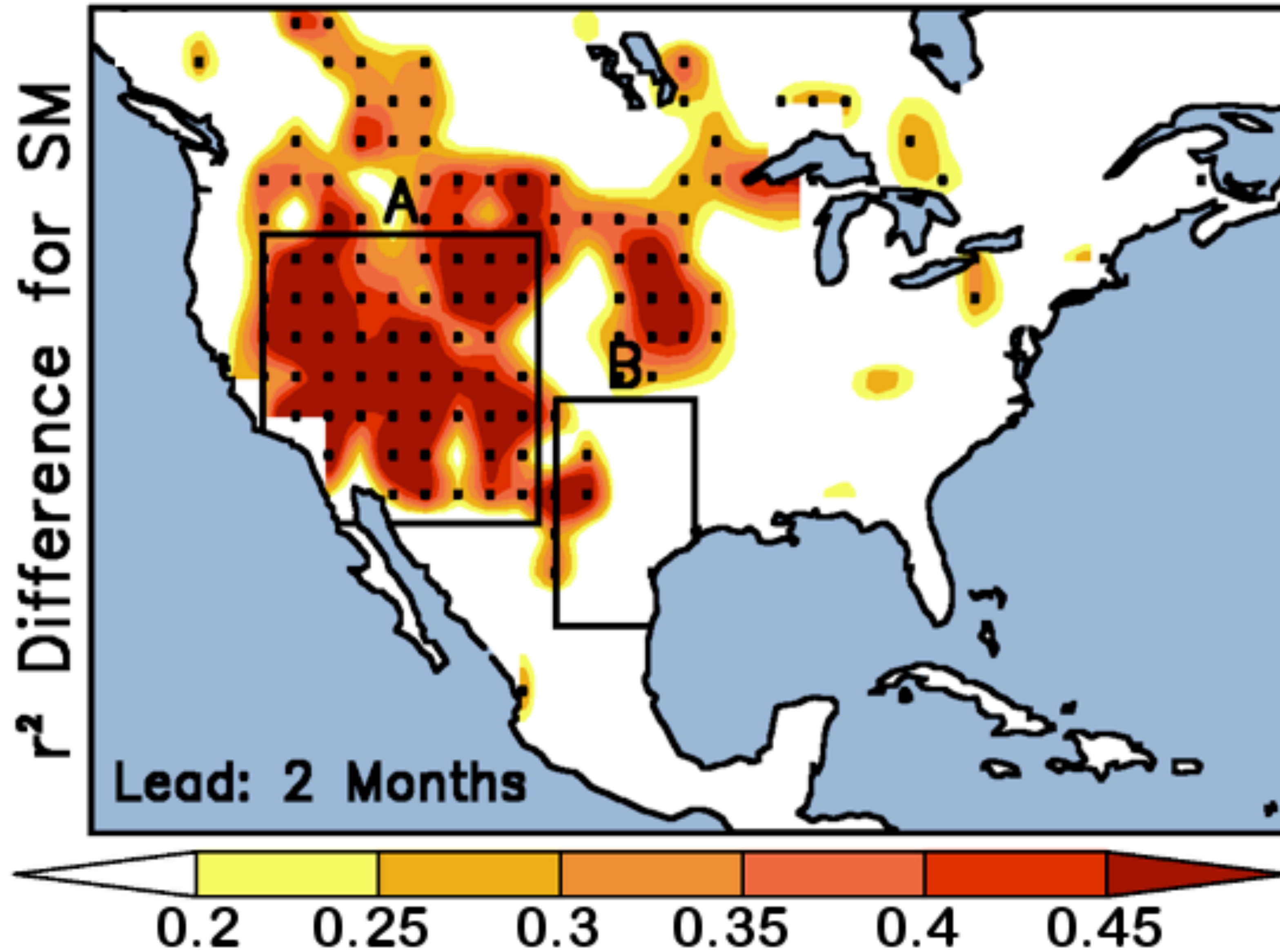


Soil moisture forecast skill

- However, the skill of soil moisture forecasts over the hot spot evaporates before two months pass.

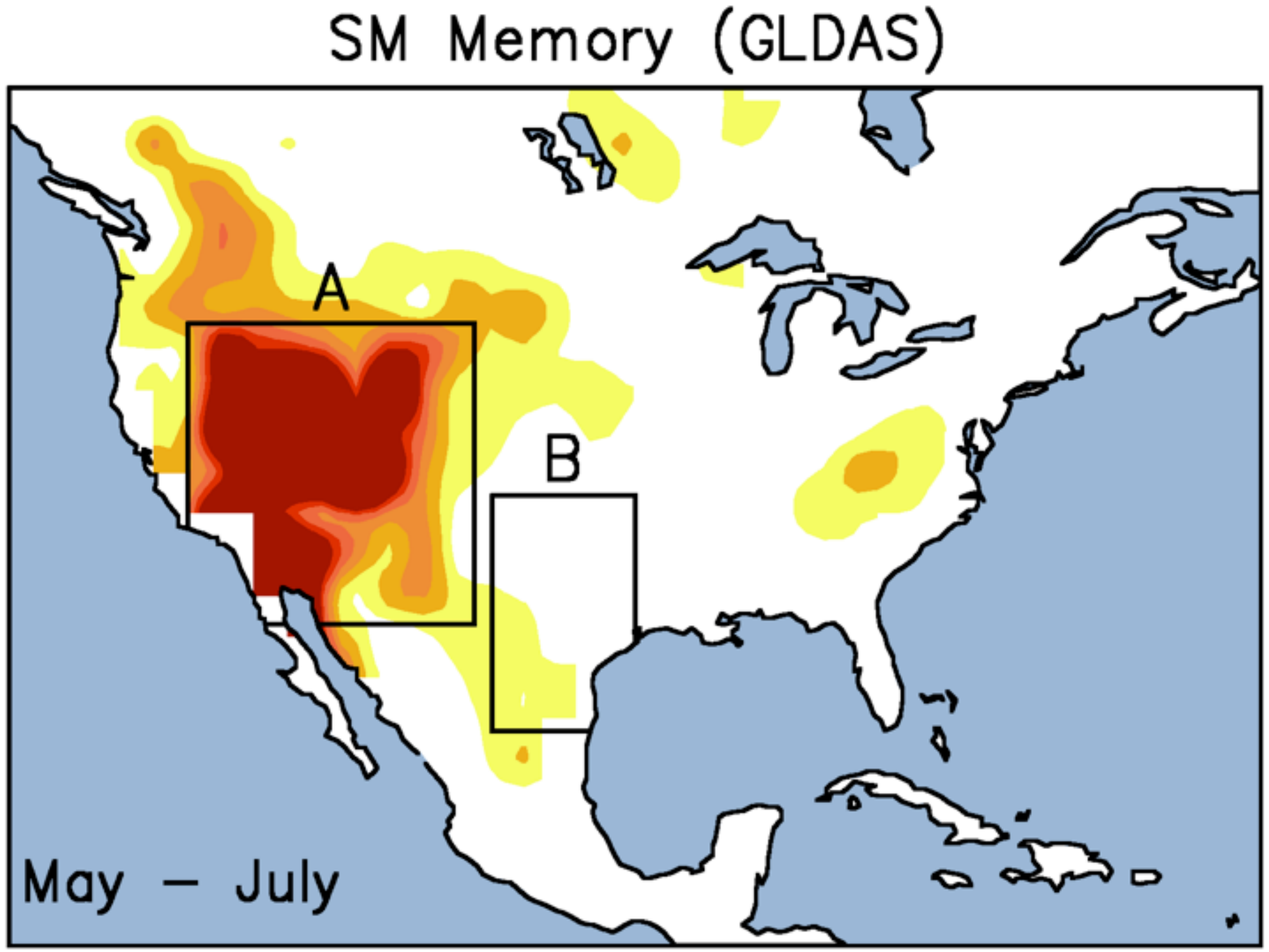
What is happening?

- Remember our key predictability ingredients: coupling, variability and <u>memory</u>



Low soil moisture memory

- As we saw, there seems to be weak soil moisture memory over the hot spot.
- On the other hand, memory is very strong over the west during summer.



An ingredient is missing

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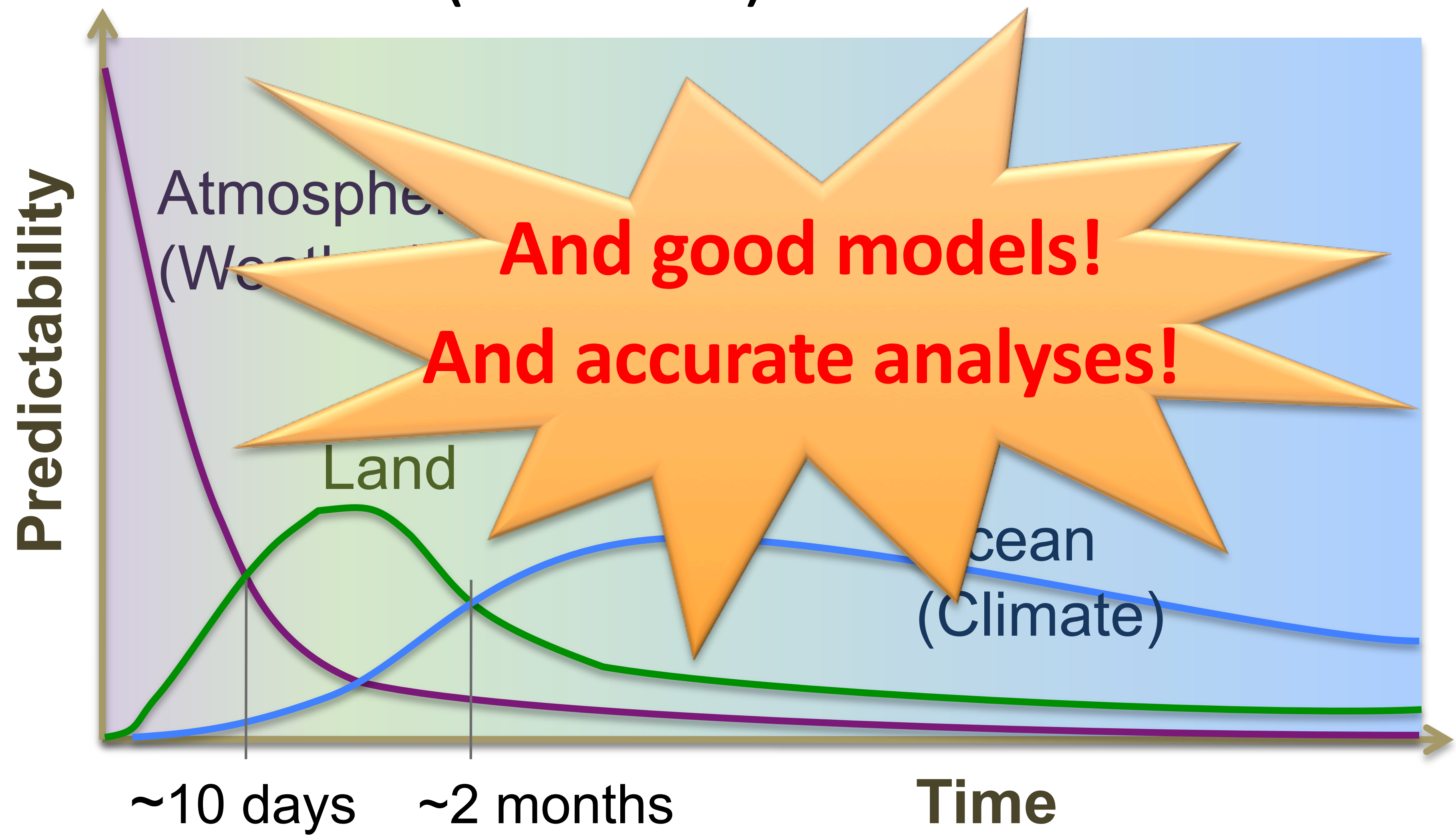

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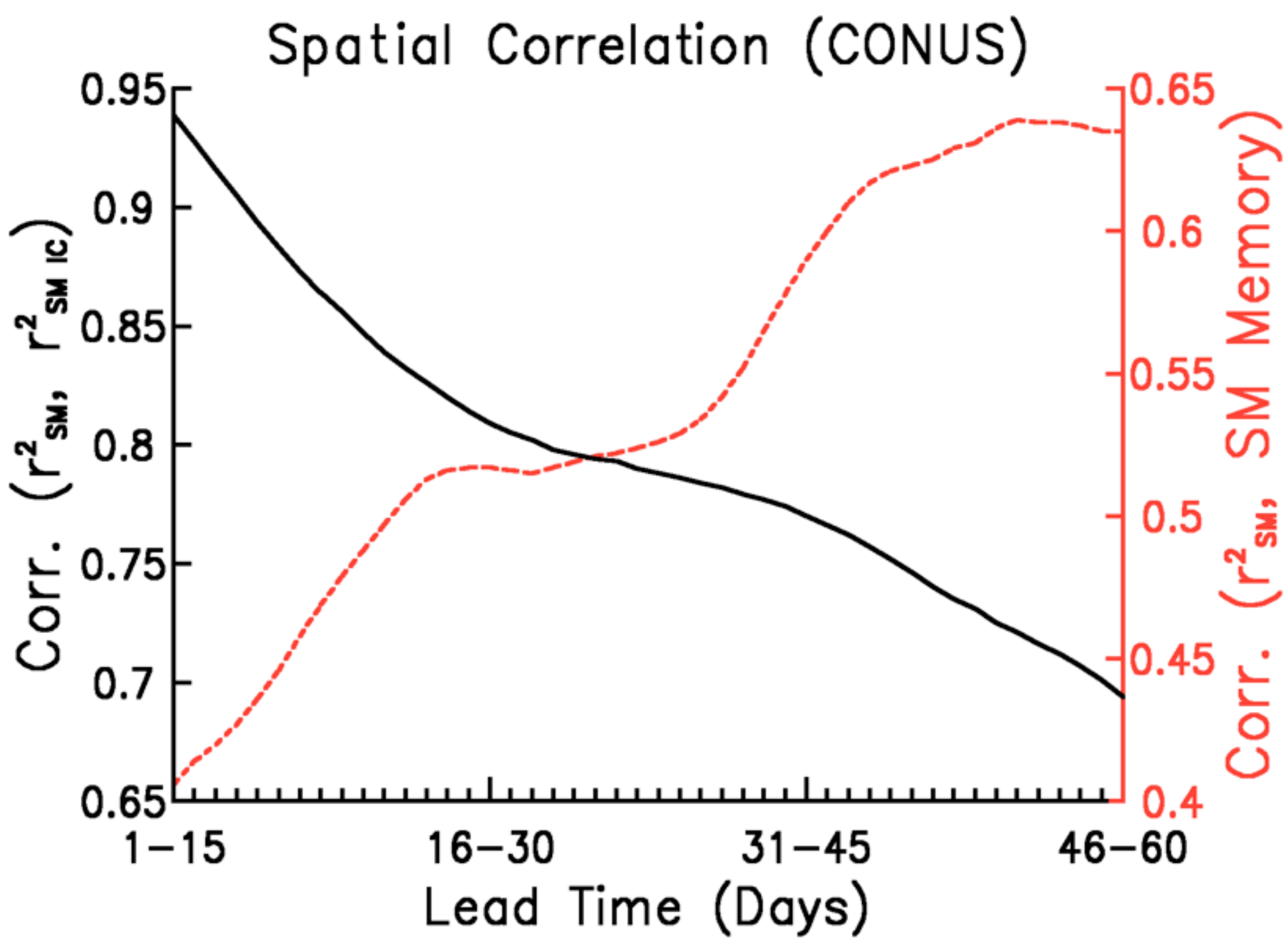
ICs versus memory

- Early in seasonal forecasts, the pattern of soil moisture forecast skill looks like the pattern of initial soil moisture quality – reflects on the quality of LDAS.



- As time goes on, the skill pattern begins to resemble soil moisture memory. And temperature skill follows soil moisture skill in summer.

Guo, Z., and P. A. Dirmeyer, 2014: Impacts of soil moisture initialization on subseasonal forecast skill. *Geophys. Res. Lett.*, (submitted).

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- Coupling and data assimilation affect memory; not just a land model problem.
- Prediction experiments have shown initial land states can improve subseasonal forecasts, but under-representation of observed memory may be a barrier to realizing predictability as forecast skill.

To do:

- Add SCAN, other soil moisture data to analysis of memory to increase density (US), coverage (global).
- Quantify the effect of spatial scale on these estimates (can be accomplished with observational soil moisture data only).
- Expand to coupling metrics (soil moisture / surface flux / atmospheric state relationships)
- "Confront" models with these metrics [GEWEX]

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